

CAAP Quarterly Report

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Prepared for: *U.S. DOT Pipeline and Hazardous Materials Safety Administration*

Project Title: Brain-Inspired Learning Framework to Bridging Information, Uncertainty and Human-Machine Decision-Making for Decoding Variance in Pipeline Computational Models

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For quarterly period ending: *Jan 7th, 2020*

Business and Activity Section

(a) Generated Commitments

Some purchase of steel plates, piezoelectric sensors and voltage amplifier

(b) Status Update of Past Quarter Activities

The research activities in the 5th quarter included: (i) Continuing efforts on material and structural integrity in **Task 2**; and (ii) Modeling for structural uncertainties in **Task 4**, as summarized in Section (d).

(c) Cost share activity

Cost share was from the graduate students' tuition waiver.

(d) Summary of detailed work for Tasks 2, and 4

1. Background and Objectives in the 5th Quarter

Traditionally, signal processing is mainly to capture signals and extract features to interpret structural performance to decode the variances experienced in structures. With the development of data mining and data-driven methods, more complex signals could be interpreted. The data-driven approaches could extract sensitive features from sensory data to assess the structural conditions, regardless of the complexity of physical systems. By taking advantage of history sensory data, the data-driven approaches tend to compress massive data, extract sensitive features from big data sets, with less prior physics inputs, and thus are robust to provide the key information from the complex data, which may be no longer valid for the conventional physics-based (analytical or numerical) approaches. Among the data-driven approaches, the machine learning techniques have been raising increasing attentions to data mining for engineer applications. The machine learning in general could be categorized as shallow learning, deep learning and reinforcement learning.

Thus, the research activities in this report aimed to experimentally and numerically investigate variances from material and structural integrity, and modeling and decoding variance experienced from structural uncertainties.

2. Feature Representation and Classification

Lamb wave apparently exhibits non-stationary and nonlinear behavior. Hence, selection of damage-sensitive features is crucial to assist the classification and prediction. In addition, the robustness of the feature under noise is also an essential factor for selecting features. In this study, features were extracted from frequency-, time-, or time-frequency-domains, while those damage-sensitive features were then selected in accordance with feature selection methods.

In time domain, physics-based features play an important role in Lamb wave feature extraction. Amplitude, energy, and correlation coefficient are three features which can represent the wave characteristic. The amplitude was obtained by the peak value of the damage wave packet. The energy calculated by the root mean square of wave (RMS) in the damage part was defined as

$$\text{rms} = \sqrt{\frac{1}{n} \sum_{i=1}^n e_i^2} \quad (1)$$

where n is the number of data point and e_i is the signal. The correlation coefficient under the damage state was used to compare with that of the health state.

In frequency domain, the amplitude was extracted as the features. 50 samples were generated randomly in each scenario by additive white Gaussian noise, which was used for feature extraction and feature selection.

Time-frequency domain is effective to track the change of a system and its nonlinear behavior and the conventional techniques are mostly encompassed by the Wavelet transform. It shows a good deal of potential in nonstationary signals analysis due to excellent local zooming property of

wavelet. By shifting and dilating the mother wavelet, a set of function, the signal can be decomposed which could preserve the temporal information. Meanwhile, the wavelet coefficients are obtained to weight the signal, which represents the feature of the signal. The discrete wavelet transforms of a continuous signal, $x(t)$, is defined by:

$$Wx(j, k) = \int_{-\infty}^{+\infty} x(t) 2^{\frac{j}{2}} \psi^*(2^j t - k) dt \quad (2)$$

where ψ and ψ^* are the basic function and its complex conjugate. Discrete wavelet transforms analyze the signal through decomposing it into successive low and high frequency components. By implementing a wavelet filter of particular frequency band shifts along the time axis, DWT analyzes the signal which makes the local examination of the signal become possible. The signal can be expressed as wavelet details and approximation in every level as shown

$$x(t) = \sum_{i=1}^n D_i(t) + A_n(t) \quad (3)$$

where $D_i(t)$ and $A_n(t)$ are the wavelet detail at the i^{th} level and the wavelet approximation at the n^{th} level. The frequency recursive relations are shown in **Fig. 1** for a full 5th level wavelet decomposition, called the Mallat-tree decomposition. DMeyer was chosen as the mother wavelet and six of the wavelet coefficients were applied as the damage sensitive features.

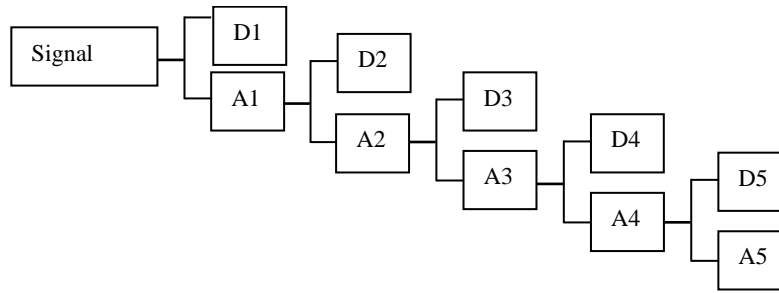


Fig. 1 Full fifth level wavelet transform

2.1 Data generated from experiment testing

This study attempted to collect data from experimental testing, which could provide certain level of uncertainty due to laboratory conditions. The test setup consists of a generator, an oscilloscope, Piezo actuators and the steel plate, as shown in **Fig. 2**. In this study, the generator submits the voltage signal, and then the piezo actuator changes the voltage signal into mechanical signal which could propagate in the steel plate. When it arrives the edge or damage of the steel plate, the signal can be reflected and received by the second actuators. In the meanwhile, the piezo actuator transfers the wave into voltage signal which can be visualized on oscilloscope.

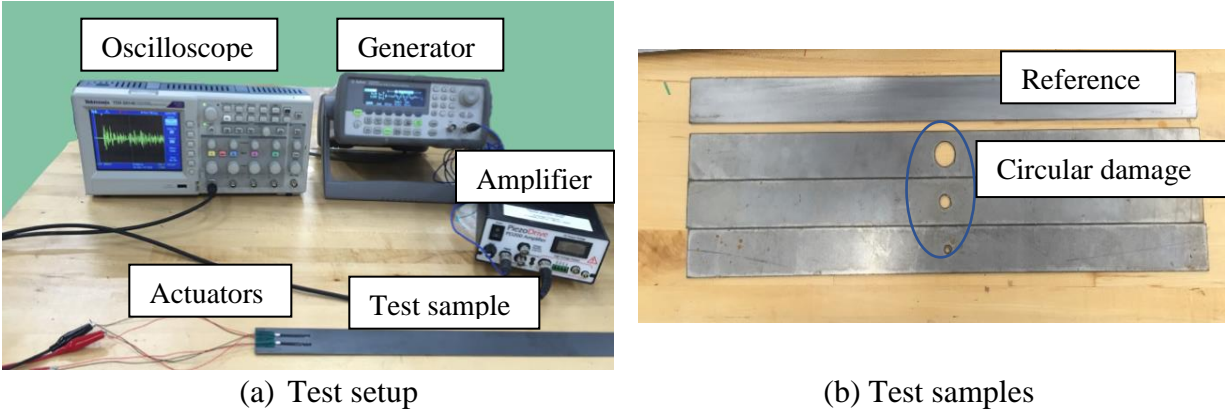


Fig. 2 Test setup

2.2 Data generated from computation modeling of lamb wave

To analyze the one-dimensional propagation of Lamb wave, we conducted FE simulation using COMSOL to model and decode different variances. Six different damage sizes were designed, ranging from 2 mm to 12 mm in length.

The prototype of the Lamb wave propagation analysis was a rectangular-shaped aluminum plate, with a dimension of 150 mm by 400 mm by 2 mm. The plate was partitioned using the mesh size with the maximum size of 4.94 mm and the smallest one of 1.65 mm. The boundary condition was free. For simplicity, damages were simulated by different types: a rectangular shaped notch, circular-shaped damage, and oval-shaped damage. All these damages were through-the-thickness located at the center of the plate, shown in **Fig. 3**. The excitation signal was a smoothed tone burst which obtained from a 5-cycle tone burst filtered through a Hanning window. The frequency used was 300 kHz. The results of the lamb wave propagated through the plate were shown in **Fig. 3**. It illustrated the wave propagated in different periods.

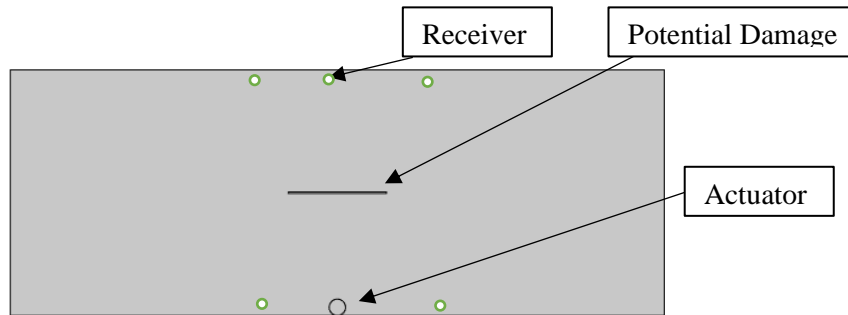
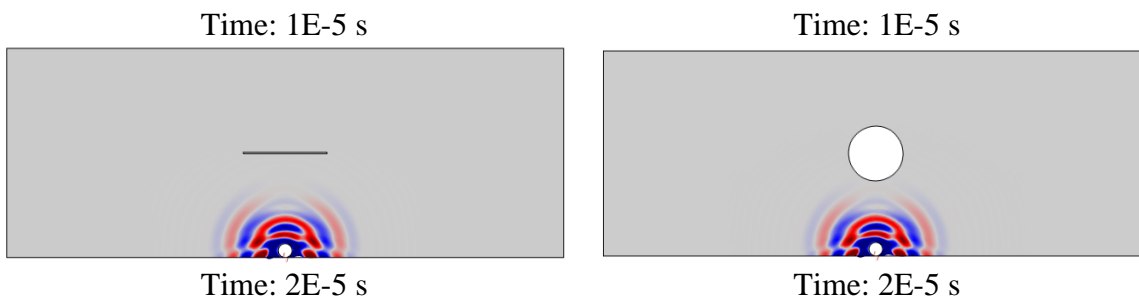
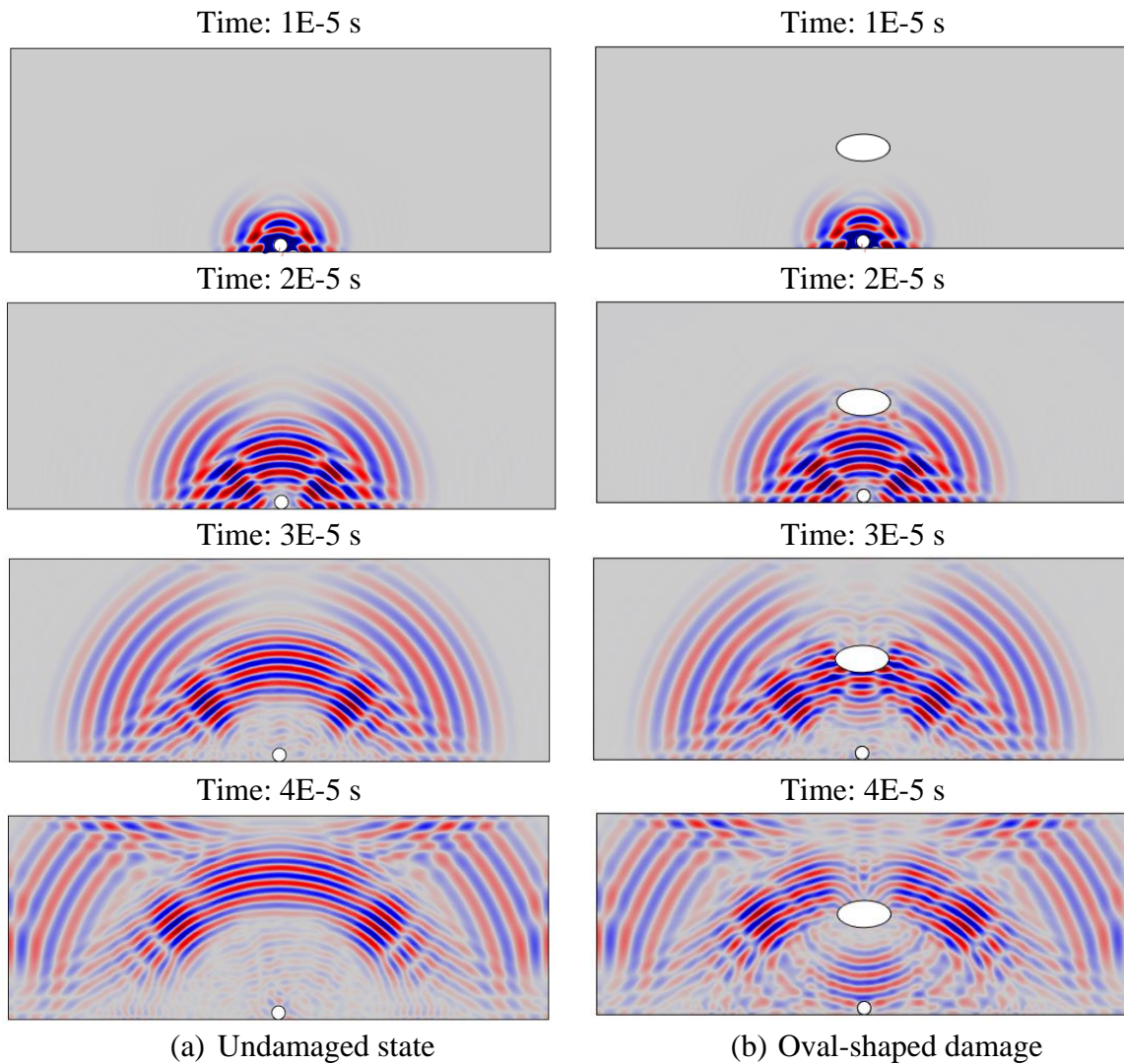


Fig. 3 Damage shape and location

The results of the lamb wave propagated through the plate were shown in **Fig. 4**. It illustrated the wave propagated in different period in the plate with different damages. At the first stage, the wave was propagated, scattered and spread upwards from the bottom of the plate. Without reaching the damage location, the contour in different states looked same. At the second stage, when the time was equal to $2E-5$, the wave arrived at the center of the plate. In undamaged state, the wave traveled continually. At damage states, the propagation of waves was blocked then some of the

waves were reflected and others were still scattered to left and right. When the wave arrived at the upper boundary of the plate, they received by the piezo actuator and returned. Noted that the initial waves and the reflected waves were interfered each other and formed complex waves.



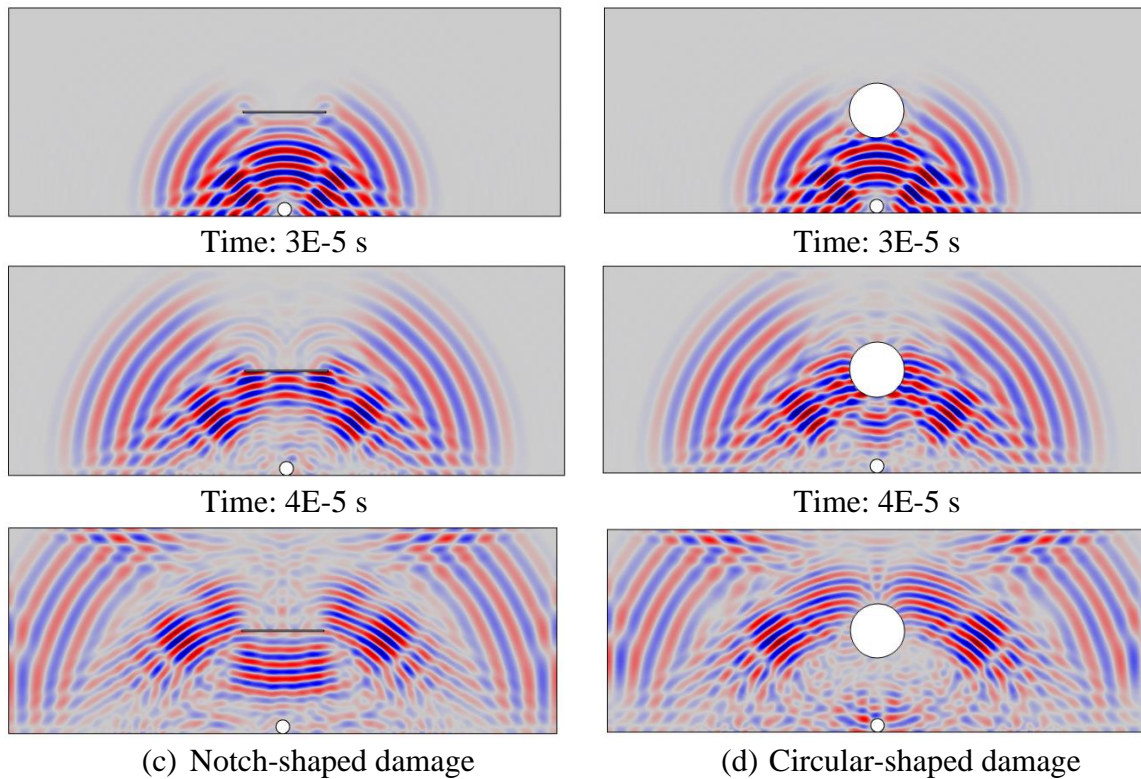


Fig. 4 Lamb wave propagation over the plate

(e) Description of any Problems/Challenges

No problems are experienced during this report period

(f) Planned Activities for the Next Quarter

The planned activities for the next quarter are listed below:

- More experimental and numerical tests for continuing efforts on material and structural integrity.
- Modeling for considering structural uncertainties.
- Characterize algorithm of machine learning and more dimensional data will be trained for the classification.